Supporting information for Mechanisms of SARS-CoV-2 Evolution Revealing Vaccine-resistant Mutations in Europe and America

Rui Wang[1], Jiahui Chen[1] and Guo-Wei Wei[1,2,3*]
[1] Department of Mathematics,
Michigan State University, MI 48824, USA.
[2] Department of Electrical and Computer Engineering,
Michigan State University, MI 48824, USA.
[3] Department of Biochemistry and Molecular Biology,
Michigan State University, MI 48824, USA.

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[*] Corresponding author. Email: weig@msu.edu

S1 Supplementary data pre-processing and feature generation methods

In this section, the workflow of the deep learning-based BFE change predictions of protein-protein interactions induced by mutations for the present SARS-CoV-2 variant analysis and prediction will be firstly introduced, which includes four steps as shown in Figure S1: (1) Data pre-processing; (2) training data preparation; (3) feature generations of protein-protein interaction complexes; (4) prediction of protein-protein interactions by deep neural networks. Next, the validation of our machine learning-based model will be demonstrated, suggesting consistent and reliable results compared to the experimental deep mutations data.

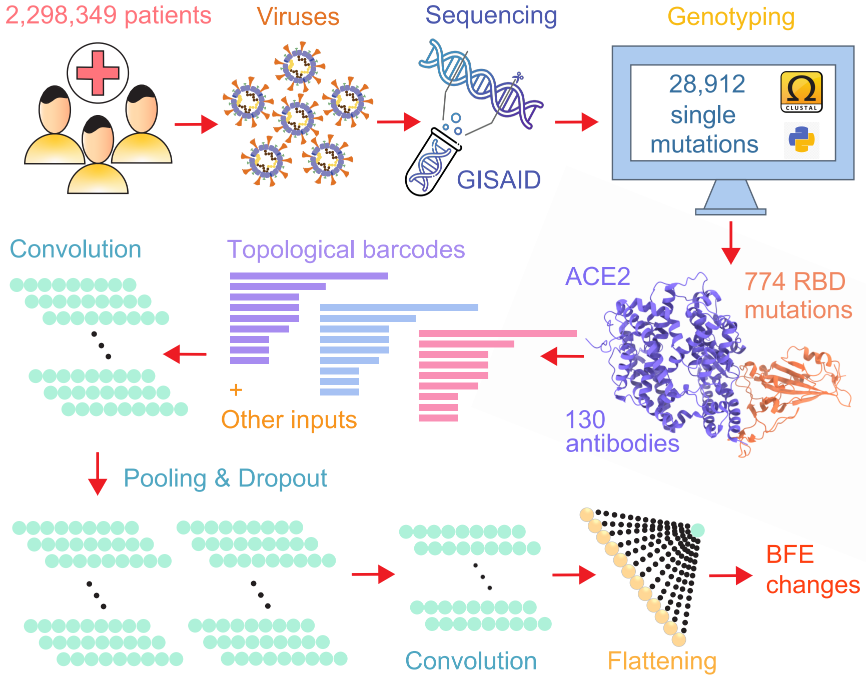

Figure S1: Illustration of genome sequence data pre-processing and BFE change predictions.

S1.1 Data pre-processing and SNP genotyping

The first step is to pre-process the original SARS-CoV-2 sequences data. In this step, a total of 1,983,328 complete SARS-CoV-2 genome sequences with high coverage and exact collection date are downloaded from the GISAID database [1] (https://www.gisaid.org/) as of August 05, 2021. Complete SARS-CoV-2 genome sequences are available from the GISAID database [1]. Next, the 1,983,328 complete SARS-CoV-2 genome sequences were rearranged according to the reference genome downloaded from the GenBank (NC_045512.2) [2], and multiple sequence alignment (MSA) is applied by using Cluster Omega with default parameters. Then, single nucleotide polymorphism (SNP) genotyping is applied to measure the genetic variations between different isolates of SARS-CoV-2 by analyzing the rearranged sequences [3,4], which is of paramount importance for tracking the genotype changes during the pandemic. The SNP genotyping captures all of the differences between patients' sequences and the reference genome, which decodes a total of 28,865 unique single mutations from 1,983,328 complete SARS-CoV-2 genome sequences. Among them, 724 non-degenerate mutations on the S protein RBD (S protein residues from 329 to 530) are detected. In this work, the co-mutation analysis is more crucial than the unique single mutation analysis. Notably, the SARS-CoV-2 unique single mutations in the world are available at Mutation Tracker. The analysis of RBD mutations is available at Mutation Analyzer.

S1.2 Methods for BFE change predictions

In this section, the process of the machine learning-based BFE change predictions is introduced. Once the data pre-processing and SNP genotyping are carried out, we will firstly proceed with the training data preparation process, which plays a key role in reliability and accuracy. A library of 130 antibodies and RBD complexes, as well as an ACE2-RBD complex, are obtained from Protein Data Bank (PDB). RBD mutation-induced BFE changes of these complexes are evaluated by the following machine learning model. According to the emergency and the rapid change of RNA virus, it is rare to have massive experimental BFE change data of SARS-CoV-2, while, on the other hand, next-generation sequencing data is relatively easy to collect. In the training process, the dataset of BFE changes induced by mutations of the SKEMPI 2.0 dataset [5] is used as the basic training set, while next-generation sequencing datasets are added as assistant training sets. The SKEMPI 2.0 contains 7,085 single- and multi-point mutations and 4,169 elements of that in 319 different protein complexes used for the machine learning model training. The mutational scanning data consists of experimental data of the binding of ACE2 and RBD induced mutations on ACE2 [6] and RBD [7,8], and the binding of CTC-445.2 and RBD with mutations on both protein [8].

Next, the feature generations of protein-protein interaction complexes are performed. The element-specific algebraic topological analysis on complex structures is implemented to generate topological bar codes [9–12]. In addition, biochemistry and biophysics features such as Coulomb interactions, surface areas, electrostatics, et al., are combined with topological features [13]. The detailed information about the topology-based models will be demonstrated in subsection S1.3. Lastly, deep neural networks for SARS-CoV-2 are constructed for the BFE change prediction of protein-protein interactions [9]. The detailed descriptions of dataset and machine learning model are found in the literature [9,14,15] and are available at TopNetmAb.

S1.3 Feature generation for machine learning model

S1.3.1 Topology features

Among all features generated for machine learning prediction, the application of topology theory makes the model to a whole new level. Those summarized as other inputs are called as auxiliary features and are described in Section S1.3.2 and S1.3.3. In this section, a brief introduction about the theory of topology will be discussed. Algebraic topology [10,11] has achieved tremendous success in many fields including biochemical and biophysical properties [12]. Special treatment should be implemented for biology applications to describe element types and amino acids in poly-peptide mathematically, which element-specific and site-specific persistent homology [14,16]. To construct the algebraic topological features on protein-protein interaction model, a series of element subsets for complex structures should be defined, which considers atoms from the mutation sites, atoms in the neighborhood of the mutation site within a certain distance, atoms from antibody binding site, atoms from antigen binding site, and atoms in the system that belong to type of {C, N, O}, $\mathcal{A}_{\rm ele}(\rm E)$. Under the element/site-specific construction, simplicial complexes is constructed on point clouds formed by atoms. For example, a set of independent $k+1$ points is from one element/site-specific set $U = \{u_0, u_1, ..., u_k\}$. The k-simplex σ is a convex hull of k+1 independent points U, which is a convex combination of independent points. For example, a 0-simplex is a point and a 1-simplex is an edge. Thus, a m-face of the k-simplex with $m+1$ vertices forms a convex hull in a lower dimension $m < k$ and is a subset of the k+1 vertices of a k-simplex, so that a sum of all its $(k-1)$–faces is the boundary of a k–simplex σ as

$$\partial_k \sigma = \sum_{i=1}^{k} (-1)^i \langle u_0, ..., \hat{u}_i, ..., u_k \rangle, \tag{1}$$

where $\langle u_0, ..., \hat{u}_i, ..., u_k \rangle$ consists of all vertices of σ excluding u_i. The collection of finitely many simplices is a simplicial complex. In the model, the Vietoris-Rips (VR) complex (if and only if $\mathbb{B}(u_{i_j}, r) \cap \mathbb{B}(u_{i_{j'}}, r) \neq \emptyset$

for $j, j' \in [0, k]$) is for dimension 0 topology, and alpha complex (if and only if $\cap_{u_{i_j} \in \sigma} \mathbb{B}(u_{i_j}, r) \neq \emptyset$) is for point cloud of dimensions 1 and 2 topology [12].

The k-chain c_k of a simplicial complex K is a formal sum of the k-simplices in K, which is $c_k = \sum \alpha_i \sigma_i$, where α_i is coefficients and is chosen to be $\mathbb{Z}_2$. Thus, the boundary operator on a k-chain c_k is

$$\partial_k c_k = \sum \alpha_i \partial_k \sigma_i, \tag{2}$$

such that $\partial_k : C_k \to C_{k-1}$ and follows from that boundaries are boundaryless $\partial_{k-1}\partial_k = \emptyset$. A chain complex is

$$\cdots \xrightarrow{\partial_{i+1}} C_i(K) \xrightarrow{\partial_i} C_{i-1}(K) \xrightarrow{\partial_{i-1}} \cdots \xrightarrow{\partial_2} C_1(K) \xrightarrow{\partial_1} C_0(K) \xrightarrow{\partial_0} 0, \tag{3}$$

as a sequence of complexes by boundary maps. Therefore, the Betti numbers are given as the ranks of kth homology group H_k as $\beta_k = \text{rank}(H_k)$, where $H_k = Z_k/B_k$, k-cycle group Z_k and the k-boundary group B_k. The Betti numbers are the key for topological features, where β_0 gives the number of connected components, such as number of atoms, β_1 is the number of cycles in the complex structure, and β_2 illustrates the number of cavities. This presents abstract properties of the 3D structure.

Finally, only one simplicial complex couldn't give the whole picture of the protein-protein interaction structure. A filtration of a topology space is needed to extract more properties. A filtration is a nested sequence such that

$$\emptyset = K_0 \subseteq K_1 \subseteq \cdots \subseteq K_m = K. \tag{4}$$

Each element of the sequence could generate the Betti numbers $\{\beta_0, \beta_1, \beta_2\}$ and consequentially, a series of Betti numbers in three dimensions is constructed and applied to be the topological fingerprints in Figure S1.

S1.3.2 Residue-level features

Mutation site neighborhood amino acid composition Neighbor residues are the residues within 10 Å of the mutation site. Distances between residues are calculated based on residue C_α atoms. Six categories of amino acid residues are counted, which are hydrophobic, polar, positively charged, negatively charged, special cases, and pharmacophore changes. The count and percentage of the 6 amino acid groups in the neighbor site are regrading as the environment composition features of the mutation site. The sum, average, and variance of residue volumes, surface areas, weights, and hydropathy scores are used but only the sum of charges is included.

pKa shifts The pKa values are calculated by the PROPKA software [17], namely the values of 7 ionizable amino acids, namely, ASP, GLU, ARG, LYS, HIS, CYS, and TYR. The maximum, minimum, sum, the sum of absolute values, and the minimum of the absolute value of total pKa shifts are calculated. We also consider the difference of pKa values between a wild type and its mutant. Additionally, the sum and the sum of the absolute value of pKa shifts based on ionizable amino acid groups are included.

Position-specific scoring matrix (PSSM) Features are computed from the conservation scores in the position-specific scoring matrix of the mutation site for the wild type and the mutant as well as their difference. The conservation scores are generated by PSI-BLAST [18].

Secondary structure The SPIDER2 software is used to compute the probability scores for residue torsion angle and residues being in a coil, alpha helix, and beta strand based on the sequences for the wild type and the mutant [19].

S1.3.3 Atom-level features

Seven groups of atom types, including C, N, O, S, H, all heavy atoms, and all atoms, are considered when generating the element-type features. Meanwhile, other three atom types, i.e., mutation site atoms, all heavy atoms, and all atoms, are used when generating the general atom-level features.

Surface areas Atom-level solvent excluded surface areas are computed by ESES [20].

Partial changes Partial change of each atom is generated by pdb2pqr software [21] using the Amber force field [22] for wild type and CHARMM force field [23] for mutant. The sum of the partial charges and the sum of absolute values of partial charges for each atomic group are collected.

Atomic pairwise interaction interactions Coulomb energy of the ith single atom is calculated as the sum of pairwise coulomb energy with every other atom as

$$C_i = \sum_{j,j\neq i} k_e \frac{q_i q_j}{r_{ij}}, \tag{5}$$

where k_e is the Coulomb's constant, r_{ij} is the distance of ith atom to jth atom, and q_i is the charge of ith atom. The van der Waals energy of the ith atom is modeled as the sum of pairwise Lennard-Jones potentials with other atoms as

$$V_i = \sum_{j,j\neq i} \epsilon \Big[\big(\frac{r_i + r_j}{r_{ij}}\big)^{12} - 2\big(\frac{r_i + r_j}{r_{ij}}\big)^{6} \Big], \tag{6}$$

where ϵ is the depth of the potential well, and r_i is van der Waals radii.

In atomic pairwise interaction, 5 groups (C, N, O, S, and all heavy atoms) are counted both for Coulomb interaction energy and van der Waals interaction energy.

Electrostatic solvation free energy Electrostatic solvation free energy of each atom is calculated using the Poisson-Boltzmann equation via MIBPB [24] and are summed up by atom groups.

S2 Supplementary machine learning methods

The topology-based network model for BFE change predictions induced mutations on SARS-CoV-2 studying applies a deep neural network structure. Similar approaches have been widely implemented in the energy prediction of protein-ligand binding [25] and protein-protein interactions [16]. The neural network method maps an input feature layer to output layer and mimics biological brains for solving problems where numerous neuron units are involved and weights of neurons are updated by backpropagation methods. To make more complicated structure in order to extract abstract properties, more layers and more neurons in each layer can be constructed. In the training process, optimization methods are applied to avoid overfitting issue, such as dropout methods [26] that a partial of computed neurons of each layer is dropped. For the model cross validations, the Pearson correlations of 10-fold cross validations is 0.864 and root mean square error is 1.019 kcal/mol.

S2.1 Deep learning algorithms

A deep neural network is a neural network methods with multi-layers (hidden layer) of neurons between the input and output layers. In each layer, the single neuron gets fully connecting with the neurons in next leyer. It should be preserve the consistency of all labels when applying the model for mutation-induced BFE change predictions. The loss function is constructed as following:

$$\underset{W,b}{\text{argmin}}\, L(W,b) = \underset{W,b}{\text{argmin}}\, \frac{1}{2} \sum_{i=1}^{N} \big(y_i - f(x_i; \{W, b\})\big)^2 + \lambda \|W\|^2 \tag{7}$$

where N is the number of samples, f is a function of the feature vector x_i parameterized by a weight vector W and bias term b, and λ represents a penalty constant.

S2.2 Optimization

The backpropagation is applied to evaluated the loss function start from the output layer and propagates backward through the network structure to update the weight vector W and bias term b. According to that the gradient calculation is required, we apply the stochastic gradient descent method with momentum which only evaluates a small part of training data and can be considered as calculating exponentially weighted averages, which is given as

$$\begin{aligned} V_i &= \beta V_{i-1} + \eta \nabla_{W_i} L(W_i, b_i) \\ W_{i+1} &= W_i - V_i, \end{aligned} \tag{8}$$

where W_i is the parameters in the network, $L(W_i, b_i)$ is the objective function, η is the learning rate, X and y are the input and target of the training set, and $\beta \in [0, 1]$ is a scalar coefficient for the momentum term. The momentum term involved accelerates the converging speed.

S3 Supplementary validation

In the main content, we briefly summarized validations of our machine learning predictions and experimental data. For large quantitative validations, we compared the BFE change prediction for mutations on S protein RBD to the experimental deep mutational enrichment data on RBD binding to human ACE2 and CTC-445.2 induced by RBD mutations [8, 9, 13]. To make these validations, we eliminated the experimental deep mutational enrichment data of RBD binding to human ACE2 and CTC-445.2 from the training sets and set them as testing sets, which have 1539 and 1500 samples, respectively. In the validation of RBD and CTC-445.2 complex, there is a very high correlation between the enrichment data and machine learning predictions, as well as the validation of RBD binding to ACE2, with Pearson correlations are 0.69 and 0.70, respectively. The deep mutational enrichment data can give a proportional descriptor of the affinity strength of protein-protein interactions induced by mutations. The machine learning methods, however, gives stable and equalized evaluations, while experimental data might be different dramatically due to conditions and environments.

In addition, we compared our machine learning results with other experimental data, which are escape fraction, pseudovirus infection changes, and IC_{50} fold changes [9]. In the comparison of 35 cases to experimental escape fractions on RBD binding to clinical trial antibodies induced by emerging mutations, our machine learning predictions have a Pearson correlation of 0.80. Especially, those high escaping mutations E484K and E484Q on LY-CoV555, and mutations K417T and K417N on LY-CoV016, are indicated by both our predictions and the experimental data [9]. We also use the pattern comparisons of our prediction to experimental data. Lastly, we collected experimental data from different literature [27–30]. According to variations from different research groups, they were summarized in increasing/decreasing patterns of emerging variant (including co-mutations) impacts on antibody therapies in clinical trials. In total there are 20 pattern comparisons with an excellent agreement between various experimental data and our predictions, except for a minor discrepancy [9].

S4 Supplementary table

Table S1 shows the top 30 most observed S protein RBD mutations up to October 20, 2021.

S5 Supplementary figures

Time evolution of vaccination rate and the frequency of Y449S in CH and RO from December 26, 2020, to October 22, 2021.

Table S1: The top 30 most observed S protein RBD mutations. Here, BFE change refers to the BFE change for the S protein and human ACE2 complex induced by a single-site S protein RBD mutation. A positive mutation-induced BFE change strengthens the binding between S protein and ACE2, which results in more infectious variants. The count of antibody disruption represents the number of antibodies and S protein complexes disrupted by a specific mutation. Here, an antibody and S protein complex is regarded as disrupted if its binding affinity is reduced by more than 0.3 kcal/mol [31]. In addition, we calculate the antibody disruption ratio (%), which is the ratio of the number of disrupted antibody and S protein complexes over 130 known complexes. Ranks are computed from 737 observed RBD mutations.

Mutation	Worldwide		BFE change		Antibody disruption		
	Count	Rank	Change	Rank	Count	Ratio	Rank
L452R	972148	1	0.5752	33	39	30.0	121
T478K	946831	2	0.9994	3	2	1.54	651
N501Y	810997	3	0.5499	35	24	18.46	196
E484K	107739	4	0.0946	303	38	29.23	129
K417T	54233	5	0.0116	475	37	28.46	131
S477N	33969	6	0.0180	464	0	0.0	726
N439K	18464	7	0.1792	176	11	8.46	321
K417N	10732	8	0.1661	193	53	40.77	81
F490S	6161	9	0.4406	59	51	39.23	88
S494P	5527	10	0.0902	314	62	47.69	64
E484Q	4673	11	0.0057	484	30	23.08	163
R346K	4551	12	0.1234	253	6	4.62	442
N440K	4466	13	0.6161	27	0	0.0	723
L452Q	3235	14	0.9802	4	27	20.77	174
A520S	3226	15	0.1495	218	3	2.31	559
G446V	2547	16	0.1583	202	9	6.92	355
A522S	2527	17	0.1283	245	2	1.54	631
N501T	2327	18	0.4514	54	17	13.08	244
R357K	2006	19	0.1393	231	5	3.85	464
S477I	1774	20	-0.0002	500	2	1.54	660
A522V	1620	21	0.0705	355	1	0.77	663
V367F	1598	22	0.1764	178	0	0.0	725
V367L	1520	23	0.0465	399	0	0.0	728
A475V	1458	24	0.3069	104	10	7.69	333
P384L	1437	25	0.2681	115	18	13.85	241
N440S	1363	26	0.1499	216	2	1.54	598
A411S	1266	27	0.5023	46	11	8.46	319
D427N	1253	28	-0.1133	618	1	0.77	679
Y449S	1193	29	-0.8112	708	85	65.38	18
P479S	1182	30	0.3844	77	3	2.31	552

S6 Supplementary data

The Supplementary_Data.zip contains four files as listed in the following subsection.

S6.0.1 Disrupted antibodies

File antibodies_disruptmutation.csv shows the name of antibodies disrupted by mutations.

S6.0.2 List of antibodies

File antibodies.csv lists the Protein Data Bank (PDB) IDs for all of the 130 SARS-CoV-2 antibodies.

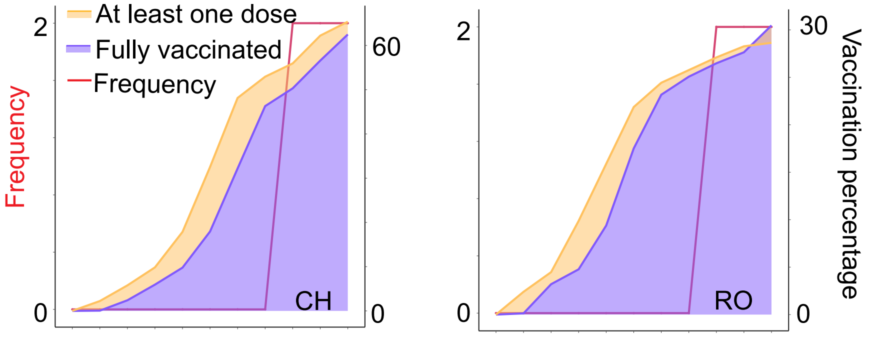

Figure S2: Time evolution of vaccination rate and the frequency of Y449S in Switzerland (CH) and Romania (RO) from December 26, 2020, to October 22, 2021. The data is collected per 30-day. The red line shows the frequency of mutation Y449S. The orange and purple areas represent at least one dose rate and fully vaccinated rate in each country.

S6.0.3 SNPs

File RBD_comutation_residue_10202021.csv lists all of the SNPs of RBD co-mutations.

S6.0.4 Non-degenerate RBD co-mutations

File Track_Comutation_10202021.xlsx records all of the non-degenerate RBD co-mutations with their frequencies, antibody disruption counts, total BFE changes, and the first detection dates and countries.

References

[1] Yuelong Shu and John McCauley. GISAID: Global initiative on sharing all influenza data–from vision to reality. *Eurosurveillance*, 22(13):30494, 2017.

[2] Fan Wu, Su Zhao, Bin Yu, Yan-Mei Chen, Wen Wang, Zhi-Gang Song, Yi Hu, Zhao-Wu Tao, Jun-Hua Tian, Yuan-Yuan Pei, et al. A new coronavirus associated with human respiratory disease in China. *Nature*, 579(7798):265–269, 2020.

[3] Changchuan Yin. Genotyping coronavirus SARS-CoV-2: methods and implications. *Genomics*, 112(5):3588–3596, 2020.

[4] Sobin Kim and Ashish Misra. Snp genotyping: technologies and biomedical applications. *Annu. Rev. Biomed. Eng.*, 9:289–320, 2007.

[5] Justina Jankauskaitė, Brian Jiménez-García, Justas Dapkūnas, Juan Fernández-Recio, and Iain H Moal. SKEMPI 2.0: an updated benchmark of changes in protein–protein binding energy, kinetics and thermodynamics upon mutation. *Bioinformatics*, 35(3):462–469, 2019.

[6] Erik Procko. The sequence of human ace2 is suboptimal for binding the s spike protein of sars coronavirus 2. *BioRxiv*, 2020.

[7] Tyler N Starr, Allison J Greaney, Sarah K Hilton, Daniel Ellis, Katharine HD Crawford, Adam S Dingens, Mary Jane Navarro, John E Bowen, M Alejandra Tortorici, Alexandra C Walls, et al. Deep mutational scanning of SARS-CoV-2 receptor binding domain reveals constraints on folding and ACE2 binding. *Cell*, 182(5):1295–1310, 2020.

[8] Thomas W Linsky, Renan Vergara, Nuria Codina, Jorgen W Nelson, Matthew J Walker, Wen Su, Christopher O Barnes, Tien-Ying Hsiang, Katharina Esser-Nobis, Kevin Yu, et al. De novo design of potent and resilient hACE2 decoys to neutralize SARS-CoV-2. *Science*, 370(6521):1208–1214, 2020.

[9] Jiahui Chen, Kaifu Gao, Rui Wang, and Guo-Wei Wei. Revealing the threat of emerging SARS-CoV-2 mutations to antibody therapies. *Journal of Molecular Biology*, 433(7744), 2021.

[10] Gunnar Carlsson. Topology and data. *Bulletin of the American Mathematical Society*, 46(2):255–308, 2009.

[11] Herbert Edelsbrunner, David Letscher, and Afra Zomorodian. Topological persistence and simplification. In *Proceedings 41st annual symposium on foundations of computer science*, pages 454–463. IEEE, 2000.

[12] Kelin Xia and Guo-Wei Wei. Persistent homology analysis of protein structure, flexibility, and folding. *International journal for numerical methods in biomedical engineering*, 30(8):814–844, 2014.

[13] Jiahui Chen, Kaifu Gao, Rui Wang, and Guo-Wei Wei. Prediction and mitigation of mutation threats to COVID-19 vaccines and antibody therapies. *Chemical Science*, 12(20):6929–6948, 2021.

[14] Jiahui Chen, Rui Wang, Menglun Wang, and Guo-Wei Wei. Mutations strengthened SARS-CoV-2 infectivity. *Journal of molecular biology*, 432(19):5212–5226, 2020.

[15] Rui Wang, Yuta Hozumi, Changchuan Yin, and Guo-Wei Wei. Mutations on COVID-19 diagnostic targets. *Genomics*, 112(6):5204–5213, 2020.

[16] Menglun Wang, Zixuan Cang, and Guo-Wei Wei. A topology-based network tree for the prediction of protein–protein binding affinity changes following mutation. *Nature Machine Intelligence*, 2(2):116–123, 2020.

[17] Delphine C Bas, David M Rogers, and Jan H Jensen. Very fast prediction and rationalization of pka values for protein–ligand complexes. *Proteins: Structure, Function, and Bioinformatics*, 73(3):765–783, 2008.

[18] Stephen F Altschul, Thomas L Madden, Alejandro A Schäffer, Jinghui Zhang, Zheng Zhang, Webb Miller, and David J Lipman. Gapped blast and psi-blast: a new generation of protein database search programs. *Nucleic acids research*, 25(17):3389–3402, 1997.

[19] Yuedong Yang, Rhys Heffernan, Kuldip Paliwal, James Lyons, Abdollah Dehzangi, Alok Sharma, Jihua Wang, Abdul Sattar, and Yaoqi Zhou. Spider2: A package to predict secondary structure, accessible surface area, and main-chain torsional angles by deep neural networks. In *Prediction of protein secondary structure*, pages 55–63. Springer, 2017.

[20] Beibei Liu, Bao Wang, Rundong Zhao, Yiying Tong, and Guo-Wei Wei. Eses: software for e ulerian solvent excluded surface, 2017.

[21] Todd J Dolinsky, Jens E Nielsen, J Andrew McCammon, and Nathan A Baker. Pdb2pqr: an automated pipeline for the setup of poisson–boltzmann electrostatics calculations. *Nucleic acids research*, 32(suppl_2):W665–W667, 2004.

[22] David A Case, Tom A Darden, Thomas E Cheatham, Carlos L Simmerling, Junmei Wang, Robert E Duke, Ray Luo, MRCW Crowley, Ross C Walker, Wei Zhang, et al. Amber 10. Technical report, University of California, 2008.

[23] Bernard R Brooks, Charles L Brooks III, Alexander D Mackerell Jr, Lennart Nilsson, Robert J Petrella, Benoît Roux, Youngdo Won, Georgios Archontis, Christian Bartels, Stefan Boresch, et al. Charmm: the biomolecular simulation program. *Journal of computational chemistry*, 30(10):1545–1614, 2009.

[24] Duan Chen, Zhan Chen, Changjun Chen, Weihua Geng, and Guo-Wei Wei. Mibpb: a software package for electrostatic analysis. *Journal of computational chemistry*, 32(4):756–770, 2011.

[25] Duc Duy Nguyen and Guo-Wei Wei. AGL-Score: Algebraic graph learning score for protein–ligand binding scoring, ranking, docking, and screening. *Journal of chemical information and modeling*, 59(7):3291–3304, 2019.

[26] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1):1929–1958, 2014.

[27] FACT SHEET FOR HEALTH CARE PROVIDERS EMERGENCY USE AUTHORIZATION (EUA) OF REGEN-COV (fda.gov).

[28] Yiska Weisblum, Fabian Schmidt, Fengwen Zhang, Justin DaSilva, Daniel Poston, Julio CC Lorenzi, Frauke Muecksch, Magdalena Rutkowska, Hans-Heinrich Hoffmann, Eleftherios Michailidis, et al. Escape from neutralizing antibodies by SARS-CoV-2 spike protein variants. *Elife*, 9:e61312, 2020.

[29] Pengfei Wang, Manoj S Nair, Lihong Liu, Sho Iketani, Yang Luo, Yicheng Guo, Maple Wang, Jian Yu, Baoshan Zhang, Peter D Kwong, et al. Antibody resistance of SARS-CoV-2 variants B. 1.351 and B. 1.1. 7. *Nature*, 10, 2021.

[30] Delphine Planas, David Veyer, Artem Baidaliuk, Isabelle Staropoli, Florence Guivel-Benhassine, Maaran Michael Rajah, Cyril Planchais, Françoise Porrot, Nicolas Robillard, Julien Puech, et al. Reduced sensitivity of SARS-CoV-2 variant delta to antibody neutralization. *Nature*, pages 1–7, 2021.

[31] Rui Wang, Jiahui Chen, Kaifu Gao, and Guo-Wei Wei. Vaccine-escape and fast-growing mutations in the United Kingdom, the United States, Singapore, Spain, India, and other COVID-19-devastated countries. *Genomics*, 113(4):2158–2170, 2021.